ANALYSIS OF C-17 DEPARTURE RELIABILITY AND MAINTENANCE METRICS

GRADUATE RESEARCH PAPER

Vincent M. Jacobs, Major, USAF

AFIT/IMO/ENS/10-07

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

AFIT/IMO/ENS/10-07

ANALYSIS OF C-17 DEPARTURE RELIABILITY AND MAINTENANCE METRICS

GRADUATE RESEARCH PROJECT

Presented to the Faculty

Department of Systems and Engineering Management

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Logistics

Vincent M. Jacobs, BS, MHR

Major, USAF

June 2010

AFIT/IMO/ENS/10-07

ANALYSIS OF C-17 DEPARTURE RELIABILITY
AND MAINTENANCE METRICS

Vincent M. Jacobs, BS, MHR
Major, USAF

Approved:

//SIGNED//	10 JUNE 2010
Shay R. Capehart (Advisor)	Date

AFIT/IMO/ENS/10-07

Abstract

This research analyzes twelve independent maintenance variables and one dependent operations variable for three USAF bases. Minitab, version 15, and Excel are used to analyze twelve months of data, from Dec 08-Nov 09. Forward selection stepwise regression and the best-subsets procedure are used to build predictive models of maintenance metrics' effect on homestation departure reliability of C-17 aircraft at Dover, McGuire, and Travis AFBs. The twelve independent maintenance variables are regressed against one output measure, departure reliability. The regression models and validation results indicate regression models selection of maintenance constraints is consistent between departure reliability and three independent variables: Total Not Mission Capable Supply Rate, Hourly Utilization Rate, and Average Number of Aircraft Possessed. The validity of these findings is limited to the time period covered, but may be generalized across C-17 aircraft at single-squadron C-17 bases within AMC.

To my wife, son, and daughter

Acknowledgements

First, I would like to thank the Lord. Placing my trust in His hands was not easy, but now I see His path on this particular journey. Next, I would like to thank my bride of the last 5 years. Without her patience and understanding, my paper would never have been completed. While I was buried in my basement for hours upon end working on my GRP, she would be upstairs taking care of the kids. Her constant encouragement was inspiring.

I would also like to whole-heartedly thank my faculty advisor, Major Shay R. Capehart. He sacrificed several days on the phone and through email trying his best to impart some grain of statistics wisdom into my simple-mind. Without his guidance, tolerance, and staying power, I would still be spinning my wheels on regression analysis.

Finally, I would like to thank Colonel Steven L. Hopkins for his support as my sponsor. His initial assistance and access into various AMC information systems was extremely useful.

Vincent M. Jacobs

Table of Contents

Page

List of Figures

Page

List of Tables

Page

I. Introduction

Background

Maintenance management metrics—sometimes called quality performance measures or indicators—are a crucial form of information used by maintenance leaders to improve the performance of maintenance organizations, equipment, and people when compared with established goals and standards (HQ AMC/A4MMP, 2008). Metrics provide a measurement of performance and capability. Leaders, supervisors and technicians must have accurate and reliable information to make decisions. Primary concerns of maintenance managers are how well the unit is meeting mission requirements, how to improve equipment performance, identifying emerging support problems, and projecting future trends (HQ AMC/A4MMP, 2008).

The overarching objective of Air Mobility Command (AMC) maintenance is to maintain aircraft and equipment in a safe, serviceable and ready condition to meet mission needs. Maintenance management metrics serve this overarching objective to evaluate/improve equipment condition, personnel skills, and long-term fleet health. Metrics are used at all levels of command to drive improved performance and adhere to well-established guidelines (HQ AMC/A4MMP, 2008). The AMC supplement to Air Force Instruction (AFI) 21-101, Aircraft and Equipment Maintenance Management (2008), states that metrics must be:

- Accurate and useful for decision-making.
- Consistent and clearly linked to goals/standards.
- Clearly understood and communicated.
- Based on a measurable, well-defined process.

Headquarters AMC (HQ AMC) staff, primarily the Operations Directorate, uses the Departure Reliability (DR) formula to calculate, analyze, and brief AMC leadership on a single

unit, multiple units, and/or the command's mission reliability (HQ AMC/A3OC, 2004). This formula is the command standard. Departure Reliability provides HQ AMC staff personnel with macro-level trend analysis information and helps identify potential failure points in the mission generation process.

Problem Statement

What effect do maintenance metrics in the mission generation process have on departure reliability ("on-time" departure rates) at C-17 bases?

Motivation & Implication

The researcher uses a background as a former maintenance officer and mobility pilot to investigate an untapped association between operations and maintenance at three C-17 bases. The goal of this paper is to analyze performance measures spanning the entire mission generation process, from preparation to launch, so base-level commanders can improve departure reliability.

AFI 10-202 Volume 6 contains conflicting information. According to the regulation, "local commanders will not use the DR formula to assess their ability/inability to produce on-time mission departures" (HQ AMC/A3OC, 2004, p. 9); however, they are to use mission reliability, or DR data, to "assess internal processes which affect their station's ability/inability to produce on-time mission departures" (HQ AMC/A3OC, 2004, p. 8). Both AFI 10-202 and 21-101 direct base-level commanders to monitor and analyze their respective performance measures, but neither regulation specifically delineates how to intermix efforts between maintenance and operations to increase DR, the supposed focus of the entire mission generation process.

> According to the AFLMA Maintenance Metrics Handbook (2009), the flying schedule is the foundation for metrics and it sets the pace for the entire wing:
> It (flying schedule) must be built on sound principles that are clearly articulated and vigorously defended by wing leadership. The flying schedule is an important document that drives consumption of Air Force resources, and the sortie is the

> focal point of consumption. Maintainers must focus on the sortie and all the events required for it to succeed. A schedule is established to attempt a smooth flow of resource use that includes people, aircraft, and consumables. Without a flying schedule, all moving parts certainly would not come together efficiently (p. 8).

Research Focus

This research focuses on bases within AMC that host a single C-17 squadron. Bases include: McGuire AFB, NJ; Travis AFB, CA; Dover AFB, DE. Each base owns multiple major weapons systems (MWS) squadrons and each base faces similar challenges in maintenance and launch capabilities. Expanding the research to wings with multiple C-17 squadrons, such as McChord AFB and Charleston AFB, does not capture the difficulties faced by units with dissimilar aircraft. For example, maintenance and logistics resources are unique limitations at Travis AFB where C-5s, C-17s, and KC-10s are parked on the flightline. Charleston and McChord AFBs have the ability to consolidate efforts and concentrate their force among a single MWS, the C-17.

Assumptions/Limitations

In this research paper, only C-17 data is compiled from three mobility wings. DR measurability is focused on unit controllable, homestation departures. Enroute and transient DR is not reflected. Although maintenance metrics are measured as unit controllable, they include performance based off of homestation, enroute, and transient C-17 aircraft.

For example, DR is calculated at McGuire AFB for 305 Air Mobility Wing (AMW) homestation C-17 aircraft departures, but does not include KC-10 or KC-135 data. However, maintenance metrics gathered from McGuire AFB includes data from homestation, enroute, and transient C-17 aircraft. This includes C-17s from other Major Commands (MAJCOMs) since homestation maintenance support is required of all enroute and transient C-17 traffic.

DR measures total "on-time" departure rates by location regardless of cause. On-time refers to the standard for departures contained within AFI 11-2C-17 Volume 3, C-17 Flying Operations--those missions departing 20 minutes before the scheduled departure time until 14 minutes after the scheduled departure time. All qualifying Tanker Airlift Control Center (TACC) tasked missions and local training missions are considered.

Systems users who input and analyze DR and maintenance metrics are assumed to be fully trained on all systems. Additionally, all data is assumed to be reported in a timely manner with accurate mission information (HQ AMC/A3OC, 2004).

Research Objective/Research Questions

The objective of this research is to use regression analysis to identify which maintenance metrics in the mission generation process have a relationship to departure reliability. The goal of this paper is to analyze performance measures spanning the entire mission generation process, from preparation to launch, so base-level commanders can improve departure reliability. This paper attempts to answer the following:

1) What are the statistical relationships between maintenance metrics and departure reliability?

2) What maintenance metrics can be focused on to enhance a mobility wing's mission generation process?

II. Literature Review

This chapter begins with an overview of performance measures and metrics within the Air Force. Specific metrics and formulas are defined. Next, a brief review of regression analysis is discussed. Also, a forecasting model and a previous Air Force Institute of Technology (AFIT) thesis are studied. And finally, FedEx's Air Operations Division is examined to see what they are doing to tie their maintenance and operations together.

Air Force Metrics

Operating conditions create the organizational environment within which management establishes strategies and tactics to achieve goals (Coyle, Bardi, & Novack, 2006). As the Air Force defines its future, it is critical that they continue to improve its efficiency and effectiveness (AFLMA, 2009). An essential element for this evaluation is metrics. According to the Air Force Logistics Management Agency (2009), “Metrics is not a bad word, but a tool for gauging where your focus, as a maintainer, needs to be directed. Good metrics are measurable and can be mapped to goals, both strategic and tactical” (p. 3). When it comes to aircraft maintenance, the Air Force depends on metrics to judge whether or not they are measuring up to the standard and succeeding in its maintenance efforts (Pendley, 2008).

Agile organizations are essentially information processing entities (Desouza & Hensgen, 2005). The performance of an organization will depend on how effectively and efficiently it processes information from its internal and external environments and applies the information towards realization of its goals and objectives. As noted by Desouza and Hensgen (2005), an agile organization will be able to (1) sense signals (data) in the environment, (2) process (construct information) them adequately, (3) mobilize knowledge-based resources and processes to take advantage of future opportunities, and (4) continuously learn and improve the operations of the organization. “In addition, an agile organization will undertake these activities in quick

time cycles and with minimal cost and effort" (p. 26). Optimal information processing is a critical element for building agile maintenance organizations (Desouza & Hensgen, 2005).

Sources defining metrics and which speak to its significance within the USAF maintenance community are vast. MAJCOM instructions, agency handbooks, policy directives, and AFIT-sponsored research are extensive albeit complicated, confusing, and sometimes contradictory. The majority of metrics are tied solely to *individual* AMC directorates, without tying them *across* directorates.

As an example, the AMC Fixed Command and Control Operations Branch, AMC/A3OC, uses only two metrics: Departure Reliability and Deviation Accountability Rate (DAR). However, the AMC Maintenance and Logistics Directorate, AMC/A4, uses a wide range of metrics. A few of those are listed in Table 1.

12-Hour Fix Rate
Aircraft Availability
Average Number of Aircraft Possessed
Break Rate
Cannibalization Rate
Delayed Discrepancies Rate
Hourly Utilization Rate
Mission Capable Rate
Total Not Mission Capable for Maintenance Rate
Total Not Mission Capable for Supply Rate

Table 1. Primary maintenance metrics

Fix Rate (FR). The FR is a leading indicator showing how well the repair process is being managed. It is a percentage of aircraft with a landing status code of 3 (includes system cap codes 3 and 4) returned to a flyable status in a certain amount of time (clock hours). Problems found by maintenance after the aircraft lands (ground found) are not considered in the fix time. The fix time stops when all Landing Status Code 3 Pilot Reported Discrepancies (PRDs) are fixed even if the aircraft remains Not Mission Capable (NMC). This metric is an excellent tool to track "dead time" in aircraft repair processes because it measures the speed of repair and equipment maintainability. The common, standard interval for this metric is 12-hours (HQ AMC/A4MMP, 2008).

$$\text{FR (\%)} = \frac{\text{“Code-3” Breaks Fixed Within 12 Hours of Landing}}{\text{Total “Code-3” Breaks}} \times 100$$

Aircraft Availability. Percentage of a fleet not in a Depot possessed status or NMC aircraft (that are unit possessed). The metric may be created at the MWS level or may be grouped by fleet (e.g., Aggregate, Bombers, Fighters) to determine “Aircraft Availability” (HQ AMC/A4MMP, 2008).

3.3.1. $\text{Availability rate} = \frac{\text{MC hours*}}{\text{Total Possessed hours**}} \times 100$

Average Number of Aircraft Possessed. The average number of aircraft possessed by a unit for a given period of time (HQ AMC/A4MMP, 2008).

Break Rate (BR). The break rate is a leading, flying-related metric. It is the percentage of aircraft that land in “Code-3” or “Alpha-3" for Mobility AF (MAF) status. This metric primarily indicates aircraft system reliability. It may also reflect the quality of aircraft maintenance performed. If Fix Rates are used as a measurement of maintainability, the Break Rate is the

complementary measurement of reliability. For true evaluation of equipment/system reliability, measurements must be taken at the system/subsystem level. It is also an excellent predictor of parts demand. Several indicators that follow break rate are Mission Capable, Total Not Mission Capable for Supply, Cannibalization Rate, and Repeat/Recur (HQ AMC/A4MMP, 2008).

$$\text{BR (\%)} = \frac{\text{Number of Sorties that Land “Code-3”}}{\text{Total Sorties Flown}} \times 100$$

<u>Cannibalization Rate (CR).</u> The CR is a leading indicator that reflects the number of cannibalization (CANN) actions (removal of a serviceable part from an aircraft or engine to replace an unserviceable part on another aircraft or engine or to fill a Readiness Spares Package (RSP)). In most cases, a cannibalization action takes place when the Logistics Readiness Squadron (LRS) cannot deliver the part when needed and mission requirements demand the aircraft be returned to an MC status. The CR is the number of cannibalization actions per total sorties flown. This rate includes all aircraft-to-aircraft, engine-to-aircraft, and aircraft/engine to RSP cannibalization actions. Since LRS relies on the back shops and depot for replenishment, this indicator can also be used, in part, to indicate back shop and depot support (HQ AMC/A4MMP, 2008).

$$\text{CR (\%)} = \frac{\text{Number of Aircraft and Engine CANNs}}{\text{Total Sorties Flown}} \times 100$$

<u>Deferred (or Delayed) Discrepancy (DD) Rate (DDR).</u> Non-grounding discrepancies should be transferred from the AFTO Form 781A to the 781K. Preplanned time changes and TCTOs are not considered delayed until the scheduled day for completion is past and the action is not completed (HQ AMC/A4MMP, 2008).

$$\text{Total DDR (\%)} = \frac{\text{Total (Snapshot) AWM + AWP Discrepancies}}{\text{Average Aircraft Possessed}}$$

Hourly Utilization (UTE) Rate. The UTE rate is a leading indicator, but serves as a yardstick for how well the maintenance organization supports the unit's mission. The UTE rate is the average number of sorties or hours flown per Primary Aerospace vehicle Authorized (PAA) per month as found in the HAF/A3OPB documents. This measurement is primarily used by operations in planning the unit's flying hour program. Maintenance uses this measurement to show usage of assigned aircraft. Since UTE rates are used for planning, actual UTE rates (computed at the end of the month) are used to evaluate the unit's monthly accomplishment against the annual plan. Typically, Combat AF (CAF) units measure the sortie UTE rate, while MAF units measure the hourly UTE rate to more accurately measure the combined performance of operations and maintenance (HQ AMC/A4MMP, 2008).

$$\boxed{\text{UTE Rate} = \frac{\text{Sorties (or hours) Flown per Month}}{\text{PAA per Month}}}$$

Mission Capable (MC) Rate. Though this is a lagging indicator, the MC rate is perhaps the best-known yardstick for measuring a unit's performance. It is the percentage of possessed hours for aircraft that are Full Mission Capable (FMC) or Partial Mission Capable (PMC) for specific measurement periods (e.g., monthly or annual). A low MC rate may indicate a unit is experiencing many hard breaks, parts supportability shortfalls, or workforce management issues. Maintenance managers should look for workers deferring repairs to other shifts, inexperienced workers, lack of parts from LRS, poor in-shop scheduling, high CANN rates, or training deficiencies. High commitment rates may also contribute to a lower MC rate. The key is to focus on negative trends and identify systemic, underlying causes. Further, the root factors of the MC rate should be measured, evaluated, and reported through the use of the TNMCM, TNMCS, and NMCB rates (HQ AMC/A4MMP, 2008).

$$MC\ (\%) = \frac{\text{FMC Hours} + \text{PMC Hours}}{\text{Possessed Hours}} \times 100$$

Total Not Mission Capable Maintenance (TNMCM) Rate. Though a lagging indicator, the TNMCM rate is perhaps the most common and useful metric for determining if maintenance is being performed quickly and accurately. It is the average percentage of possessed aircraft (calculated monthly/annually) that are unable to meet primary assigned missions for maintenance reasons. Any aircraft that is unable to meet any of its wartime missions is considered NMC. The TNMCM is the amount of time aircraft are in NMCM plus Not Mission Capable Both (NMCB) status. Maintenance managers should look for a relationship between other metrics such as R/R, BR and FR to the TNMCM Rate. A strong correlation could indicate heavy workloads (e.g., people are over tasked), poor management, training problems or poor maintenance practices. The TNMCM is also called “out for maintenance.”

$$TNMCM\ (\%) = \frac{\text{NMCM Hrs} + \text{NMCB Hrs}}{\text{Possessed Hours}} \times 100$$

Total Not Mission Capable Supply (TNMCS) Rate. Though this lagging metric may seem a “LRS responsibility” because it is principally driven by availability of spare parts, it is often directly indicative of maintenance practices. For instance, maintenance can keep the rate lower by consolidating feasible CANN actions to as few aircraft as practical. This monthly/annual metric is the average percentage of possessed aircraft that are unable to meet primary missions for supply reasons. The TNMCS rate is the time aircraft are in NMCS plus NMCB status. TNMCS is based on the number of airframes out for mission capable (MICAP) parts that prevent the airframes from performing their mission (NMCS is not the number of parts that are MICAP). Maintenance managers must closely monitor the relationship between the CR and TNMCS. TNMCS is also called "out for supply."

$$\text{TNMCS (\%)} = \frac{\text{NMCS Hrs} + \text{NMCB Hrs}}{\text{Possessed Hours}} \times 100$$

These previous performance measures are a sample of AMC/A4 metrics, however they differ from what AMC/A3OC uses and from what the Mission Reliability and Reporting System (MRSS) employs. AMC/A3OC uses MRSS to provide United States Transportation Command, AMC, other MAJCOMs, and unit commanders with the information necessary to conduct command and control (C2) and the ability to assess and improve the health of the air mobility component of the Defense Transportation System (HQ AMC/A3OC, 2004).

Departure Reliability reporting is another example illustrating the divergence in reporting procedures between maintainers and operators. For maintainers, Logistics DR is the percent of departures that are delayed because of supply, saturation, or maintenance problems, providing a measurement up to the point of an aircraft's launch regarding logistics parameters (AFLMA, 2009). Conversely, for operators, DR is a metric from preparation to execution, reflecting only if the aircraft launches on time, without consideration for deviations within the formula (HQ AMC/A3OC, 2004).

Logistics DR = ((# of Departures - # of Logistics Delays) / (# of Departures)) x 100

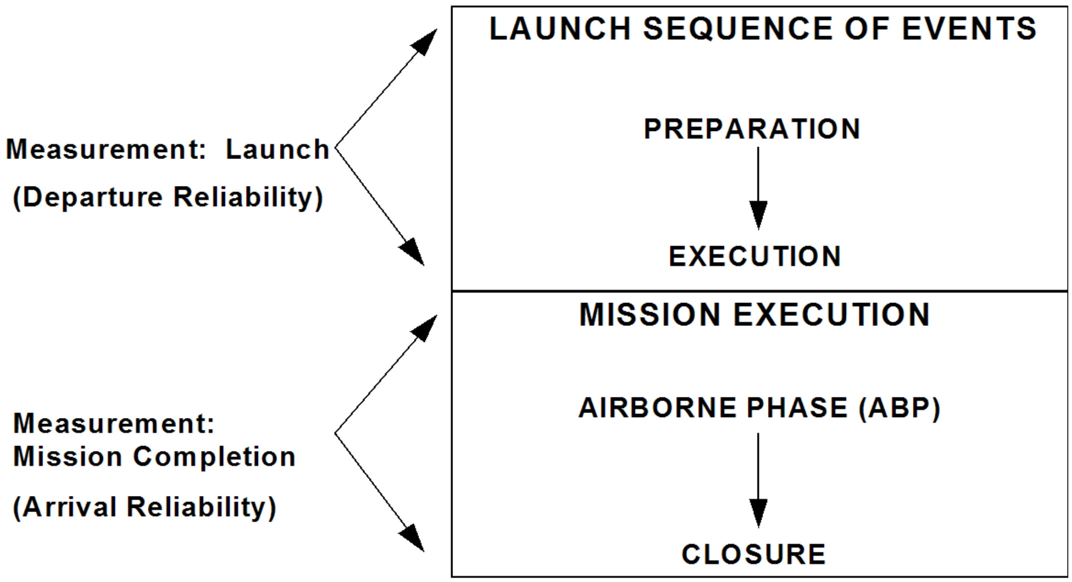


Figure 1. Mission Launch and Execution Model (HQ AMC/A3OC, 2004)

AMC/A3OC uses DR and DAR as mission reliability formulas to calculate, analyze, and brief AMC leadership on a single unit, multiple units, and/or the command's mission reliability (HQ AMC/A3OC, 2004). DR is calculated as the number of on time departures divided by the total departures for qualifying missions multiplied by 100. It is similar to Logistics DR, but does not specifically take delays into account in its formula. Instead, deviations and delays are calculated in a different metric, DAR.

DR = (On Time Departures/Total Departures) * 100

DAR = (Accountable Deviations / Departures) * 100

Thus, a coherent metric does not exist tying the maintenance and operations processes together, from scheduling to sortie launch, demonstrating the gap that is still present among two competing philosophies.

Regression Analysis

Managerial decisions are often based on the relationship between two or more variables. Sometimes a manager will rely on intuition to judge how these variables are related. However, if

data can be obtained, a statistical procedure called regression analysis can be used to develop an equation showing how the variables are related (Anderson, Sweeney, & Williams, 2008).

Regression analysis cannot be interpreted as a procedure for establishing a cause-and-effect relationship between variables. "It can only indicate how or to what extent variables are associated with each other" (Anderson, Sweeney, & Williams, 2008, p. 548). Any conclusions about cause-and-effect must be based upon the judgment of individuals most knowledgeable about the application. Therefore, concluding a cause-and effect relationship is warranted only if the analyst can provide some type of theoretical justification that the relationship is in fact causal (Anderson, Sweeney, & Williams, 2008).

Previous AFIT Thesis

Very few sources were found during the research and literature review process that specifically deal with mobility airlift assets with respect to metrics and regression analysis. However, an AFIT thesis written by Captain Charles R. Jung in 1991 came closest to mirroring this research's proposed topic.

As the problem statement in his thesis, Jung (1991) writes, "Existing production capability measurements in aircraft maintenance fail to give Strategic Air Command (SAC) maintenance managers an accurate estimation of maintenance production capability when planning maintenance support for sortie generation" (p. 3).

Jung (1991) concludes that "the most appropriate forecasting technique for this thesis application is a regression model based on the need for identification of variable relationships between maintenance constraints and production output" (p. 25).

Unfortunately, Jung (1991) finds his results to be "inconclusive as to what maintenance constraints are indicators of production capability in aircraft maintenance." Furthermore, he contends that "Maintenance production is a complex dynamic system that is not easily definable

in terms of production inputs and outputs and makes maintenance performance measurement difficult at best" (p. 116).

Similar to Jung, the researcher examined a MAJCOM's (AMC) maintenance metrics. Also, regression analysis was applied for possible relationships between independent maintenance variables and DR, the dependent variable.

Jung (1991) proposes the following research questions:

1) What are the existing measures of aircraft maintenance production capability in SAC?

2) What are the aircraft maintenance production constraints that limit or enhance production capability?

3) What are the statistical relationships between the maintenance constraints and an organization's production capability?

4) What maintenance constraints can be used in a predictive model of a maintenance organization's sortie producing capability (p. 3)?

However, unlike Jung, this research centers on the association between maintenance and operations organizations. Also, Jung's scope of research includes maintenance performance measures among several different SAC aircraft across numerous wings, whereas this research involves a single MWS at only three wings.

> Jung's suggested future research states: The results of previous research…indicate that future research in this area at the aggregate level may not be appropriate. Research at a lower level, such as one particular aircraft serial number of an aircraft system type using a significantly larger data sample over a longer period of time may prove to be profitable. The larger sample may reduce the random and cyclical variance that hindered this research. The methodology used in this thesis appears sound and could help in any future efforts. (pp. 115-116)

This research follows Jung's suggestions to research at a lower level with a significantly larger data sample; however, the research encompasses a slightly shorter 12 month period versus the 15 month timeframe Jung uses.

Air Force Forecasting Model

Developing a model may be an appropriate fit under certain situations and deliver some degree of predictability; however, models used in forecasting are sometimes flawed. According to Oliver, Johnson, White, and Arostegui (2001), the Air Force uses the Funding/Availability Multimethod Allocator for Spares (FAMMAS) model to forecast overall MC rates for each aircraft in its inventory. FAMMAS uses time-series forecasting techniques to predict overall MC rates for each MWS, using past, present, and future spares funding levels, along with the last three years of historical supply and maintenance data. Numerous operational and funding decisions are made each year based, in part, on the predictions of this model (p. 3).

Oliver et al. (2001) argue that while the FAMMAS model does an excellent job of predicting MC rates for each aircraft based on funding data and planning factors, it does not adequately consider other factors that could impact MC rates. Specifically, the FAMMAS model does not incorporate any logistics or operations-related factors into its prediction computations of MC rates, other than TNMCM/S data that act as adjustment factors in the model (Oliver, Johnson, White, & Arostegui, 2001).

Past studies have identified many other factors related to MC rates. "Unfortunately, there have been few attempts to include these different factors in the construction of a mathematical model that explains and forecasts MC rates" (Oliver et al., 2001, p. 31). While FAMMAS is an effective tool for predicting MC rates, it does not adequately consider other significant factors besides funding. Furthermore, it does not identify potential cause-and-effect relationships, especially between operations and logistics, which might be manipulated to affect future MC rates (Oliver, Johnson, White, & Arostegui, 2001).

Outside Practice-FedEx

Both the Air Force and FedEx are interested in consolidating performance measures into meaningful metrics using the balanced scorecard, developed by Kaplan and Norton in the early 1990s as a tool to translate an organization's vision and strategy into a coherent or balanced set of performance measures (Johnson, 2007). "While traditional methods focus only on financial measurements to gauge organizational performance, balanced scorecard measures focus on four key areas: customer, business processes, financial, and learning and growth" (Johnson, 2007, p. 2). The performance measures link activities at all levels to the organization's strategic objectives through a continuous chain of cause-and-effect relationships (Johnson, 2007). This permits managers at every level to monitor how other levels are performing and allows employees at each level to see how their efforts contribute to the organization's overall strategic objectives (Kaplan & Norton, 1996).

Johnson (2007) states, "Prior to implementation of the balanced scorecard, Air Force metrics were heavily focused on financial and production indicators and not on providing support to the warfighter" (p. 3). The balanced scorecard initiative was adopted to correct this deficiency and to develop a broader, more holistic view of organizational effectiveness, focused on providing the best possible support to the warfighter (Johnson, 2007). Once the logistics balanced scorecard has been fully implemented within the Air Force, it will provide the ability to view the health and welfare of Air Force logistics in a single location with drill-down capability to support management analysis and decision-making (Johnson, 2007).

FedEx Express is an example of a civilian company attempting to establish a balanced scorecard by means of the Line Maintenance Scorecard. Larry Crull, FedEx Air Operations Division manager and Lean Ops Development & Education Black Belt, was asked for his personal opinion on the link between maintenance and operations metrics. During an interview

at the FedEx Express headquarters in Memphis, TN, Larry Crull was asked, "Is there a relationship between your division's metrics and the flightline's to make FedEx more efficient?"

> Crull answered, “We have in the past had a weak relationship with our operations side but we are now improving the relationship and working jointly to improve our processes where the operations touch. This has been a shift for some to look at the other operations as our customer/suppliers and has been a slow but vital journey." (personal communication, November 4th, 2009)

Below are slides provided to the researcher by Larry Crull from a "fictional" FedEx Line Maintenance Scorecard (September 16th, 2009):

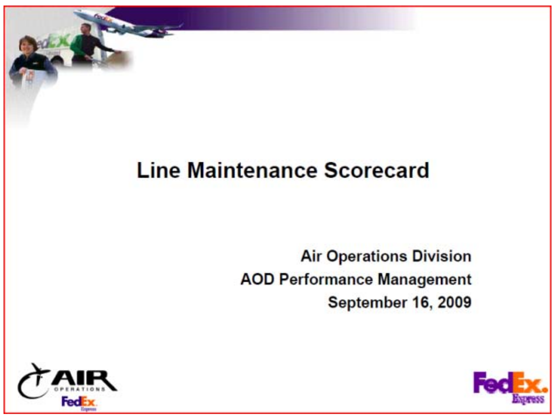


Figure 2. FedEx briefing title page

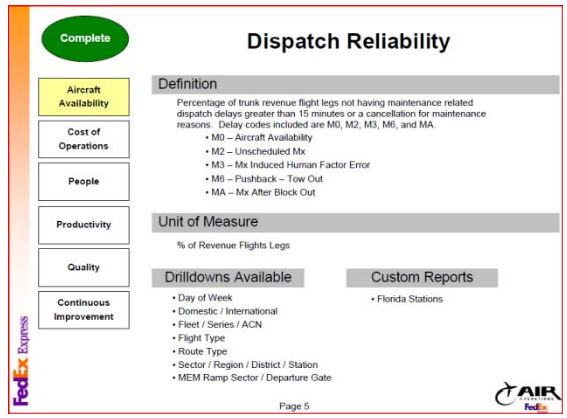


Figure 4. Aircraft Metric: Dispatch Reliability

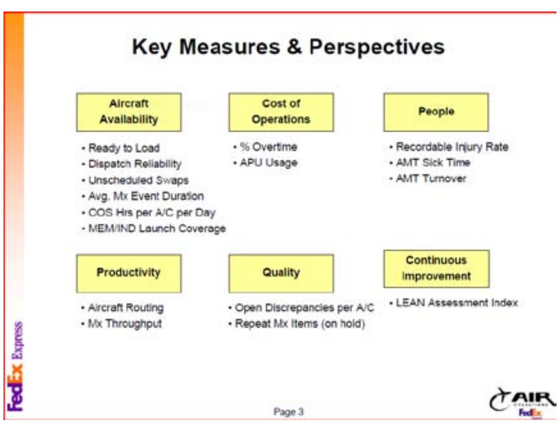


Figure 3. Key Measures/Perspectives

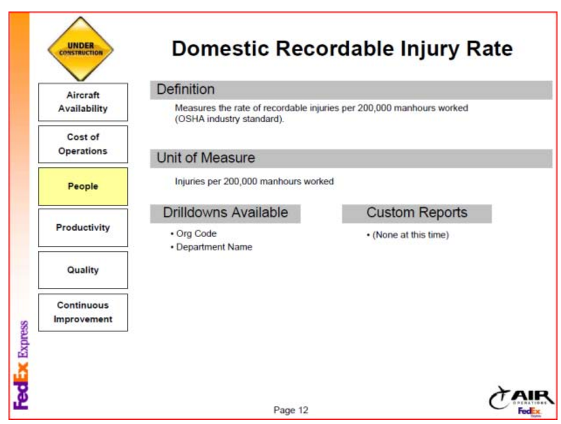


Figure 5. People Metric: Recordable Injury Rate

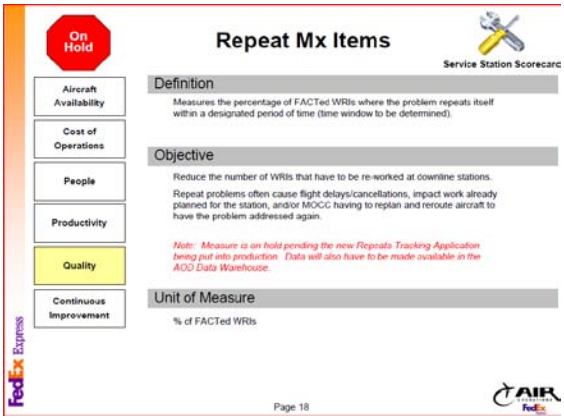


Figure 6. Quality Metric: Repeat Mx Items

Figure 7. Performance Measure Data

These slides are a prototype of what is expected in the near future at FedEx. Remaining development work includes coding changes for maintenance reorganization and final testing/validation, planned for November 30th, 2009. After final development and roll-out, FedEx plans to train all central and peripheral users and eventually establish measurable targets from historical data. Although still in its infancy, FedEx leadership places a great deal of importance on metrics through business process improvement and information technology.

III. Methodology

Multiple regression analysis enables us to understand how the dependent variable, DR, relates to the twelve independent maintenance variables. Regression analysis is conducted in accordance with *Statistics for Business and Economics, 10e* (Anderson, Sweeney, & Williams, 2008). Data is collected over a 12 month period, from December 01, 2008 until November 30, 2009, and compiled using Minitab, version 15. A computer program is the only realistic means of performing numerous computations required in multiple regression analysis (Anderson, Sweeney, & Williams, 2008).

Statistical Analysis

In regression analysis, the term *independent variable* refers to any variable being used to predict or explain the value of the dependent variable, but the term does not mean that the independent variables themselves are independent in any statistical sense (Anderson, Sweeney, & Williams, 2008). Most independent variables are correlated to some degree with one another, thus some degree of linear association between independent variables exists (Anderson, Sweeney, & Williams, 2008). Multicollinearity refers to the correlation among the independent variables. Anderson et al. (2008) warn that "if possible, every attempt should be made to avoid including variables that are highly correlated…when multicollinearity is severe, we can have difficulty interpreting the results of tests on the individual parameters" (pp. 644-645).

Although there are potential multicollinearity problems, this research develops an estimated regression equation using ten independent variables (without the dummy variables) to answer, in part, research question 1. To finish answering research question 1 and to answer question 2, forward selection regression and best-subsets regression, using all twelve independent variables, are used to identify which independent variables provide the best model.

> Anderson et al. (2008) summarizes the forward selection regression procedure as follows:
> The forward selection procedure starts with no independent variables. It adds variables one at a time using the same procedure as stepwise regression for determining whether an independent variable should be entered into the model. However, the forward selection procedure does not permit a variable to be removed from the model once it has been entered. The procedure stops if the p-value for each of the independent variables not in the model is greater than *Alpha to enter* (p. 722)

The forward selection procedure is iterative whereas the best-subsets procedure is not a one-variable-at-time procedure--it evaluates regression models involving different subsets of the independent variables (Anderson, Sweeney, & Williams, 2008). Forward selection does not guarantee that the best model for a given number of variables will be found; hence, this method is viewed as heuristics for selecting a good regression model (Anderson, Sweeney, & Williams, 2008).

> Anderson et al. (2008) describes best-subsets regression:
> …this output identifies the two best one-variable estimated regression equations, the two best two-variable equations, the two best three-variable equations, and so on. The criterion used in determining which estimated regression equations are best for any number of predictors is the value of the coefficient of determination. (p. 723)

The adjusted coefficient of determination (R^2) of both the ten-independent-variable estimated regression equation and the best model equation are then compared to each other. Next, to guard against the potential high multicollinearity, each selected independent variable's variance inflation factor (VIF) from the best model equation of the forward selection procedure is evaluated. VIF indicates the extent to which multicollinearity is present in a regression analysis. Multicollinearity is problematic because it can increase the regression coefficients, making them unstable and difficult to interpret. A VIF measures how much the variance of the estimated regression coefficients are inflated as compared to when the predictor variables are not

linearly related (LEAD Technologies, Inc., 2009). And finally, the forward selection model is compared to selected models from the best-subsets procedure to determine the best overall model.

Excel Problems and Minitab Specifics

Performing the regression analysis computations without the help of a computer can be time consuming or nearly impossible. Techniques used for regression analysis with Minitab were found in the appendices of chapters 14-16 of *Statistics for Business and Economics, 10e* (Anderson, Sweeney, & Williams, 2008). Initially, this researcher attempted to use Excel; however, Excel is not equipped standard with a stepwise regression tool in its data analysis regression package. Consequently, a special software package add-in (Pekoz, 2009) from the internet was downloaded and installed. After several compilations, several numerical inaccuracies were found in Excel as demonstrated by outputs as "#NUM!" and "65535", an Excel-ism for a t-statistic equal to infinity. This is an indication that the numerical methods used by Excel are out-of-date, and cannot be trusted (Simonoff, 2008). Simonoff argued that "these problems have been known in the statistical community for many years, going back to the earliest versions of Excel…the solution to all these problems is to perform statistical analyses using the appropriate tool--a good statistical package," and he reasoned that many packages like Minitab are available for under $100 with a Windows-type graphical user interface that are remarkably accurate and powerful (Simonoff, 2008, p. 6). Minitab was used almost exclusively after numerous compiling issues with Excel's stepwise procedure were encountered.

Sources of Data

All data is collected from two U.S. Government Information Systems (USGIS): Global Data Support System II (GDSS2) and Global Reach Logistics/A4 Information System. Both

sites require strict logon protocols and permission rights before data is obtained. Monthly data is gathered from three AMC bases over a 12 month period. DR is gleaned from GDSS2 and maintenance performance measures are collected using the Global Reach Logistics/A4 Information System.

The primary MAF C2 system for mission management and movement reporting is GDSS2 (AMC/A3OC, 2004). GDSS2 is a MAF Force-Level C2 automated system supporting mission management and execution authority for effective global air mobility mission operations. It provides MAF commanders accurate, near real-time data required for making decisions concerning the deployment, employment, and redeployment of MAF resources. GDSS2 interfaces with many other systems. Additionally, GDSS2 provides all levels of command with the same mission visibility and allows real time updates. It uses multiple applications to access and update the same database while residing on the "C2 enclave" which contains other systems required by the MAF such as the Advance Computer Flight Planning System and the Integrated Management Tool (AMC/A3OC, 2004). Within GDSS2 is the Reports Information Database Library (RIDL), used to display information over a given time period.

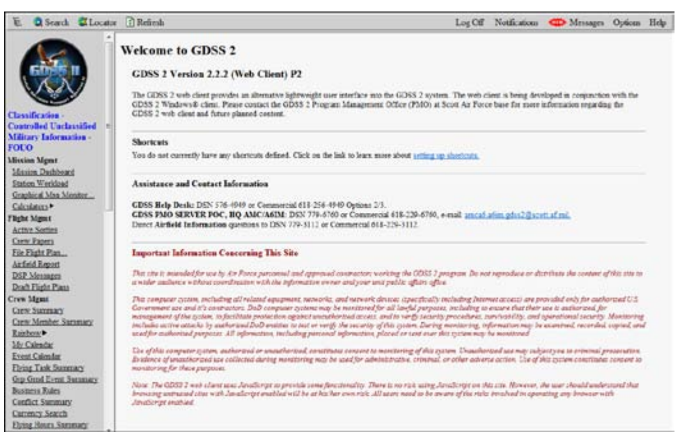
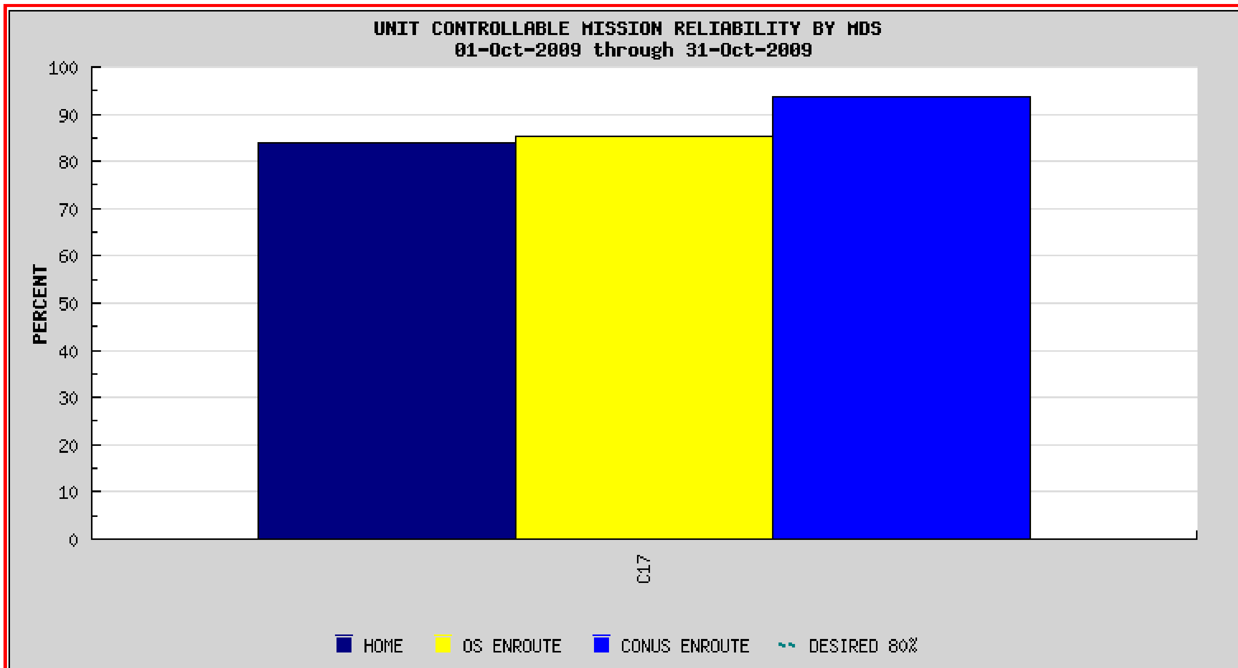


Figure 8. GDSS2 interface



	C17
HOME	84.1%
OS ENROUTE	85.3%
CONUS ENROUTE	93.5%

Figure 9. GDSS2/RIDL report

From the Global Reach Logistics/A4 Information System, the Situational Awareness Report Selector is drilled down into to obtain AMC/A4 maintenance performance measures. The information contained within the Global Reach Logistics/A4 Information System is vast with an abundance of data. For example, reports are capable of showing broad, fleet wide health across all MAJCOMs or pared down to display an individual aircraft's status.

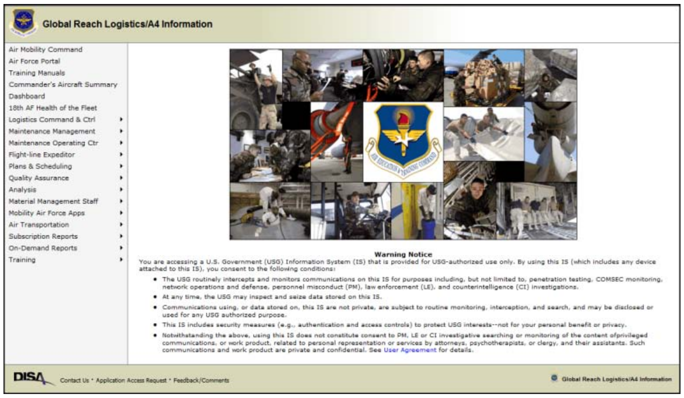


Figure 10. Global Reach Logistics/A4 Information System

Situational Awareness Report
Data Collected on 11/06/2009

	INDICATOR	COMMAND	BASE	NOV-08	DEC-08	JAN-09	FEB-09	MAR-09	APR-09	MAY-09	JUN-09	JUL-09	AUG-09	SEP-09	OCT-09
C017	MC Rate	AMC	Travis AFB	92.5	86.5	93.3	85.4	89.8	91.4	92.2	89.4	89.0	90.0	96.8	91.3
	TNMCM Rate	AMC	Travis AFB	6.4	12.4	6.7	11.2	9.7	8.5	7.0	9.9	9.7	8.6	2.9	7.6
	TNMCS Rate	AMC	Travis AFB	2.9	1.8	.7	4.4	2.9	2.7	1.2	1.2	5.1	3.3	.3	1.9
	Avg Poss	AMC	Travis AFB	12.8	13.0	12.1	12.2	11.0	12.0	12.0	11.2	11.6	10.9	11.0	11.0
	eLog21 Acft Availability	AMC	Travis AFB	91.9	86.3	86.8	80.1	76.0	84.6	84.8	76.7	79.4	75.8	82.2	77.2
	Hourly Use	AMC	Travis AFB	109.9	117.5	116.9	100.0	122.3	148.2	126.2	120.1	122.2	141.9	146.3	127.7
	CANN Rate	AMC	Travis AFB	.0	.0	.7	.0	.0	.0	.3	.0	.8	1.0	.0	.0
	Break Rate	AMC	Travis AFB	.7	1.3	1.5	1.3	1.2	.9	.3	.0	.8	1.0	.3	.4
	4 Hr Fix Rate	AMC	Travis AFB	.0	.0	75.0	.0	66.7	.0	100.0	.0	50.0	66.7	100.0	100.0
	8 Hr Fix Rate	AMC	Travis AFB	.0	50.0	75.0	33.3	66.7	100.0	100.0	.0	100.0	66.7	100.0	100.0
	12 Hr Fix Rate	AMC	Travis AFB	.0	50.0	75.0	33.3	100.0	100.0	100.0	.0	100.0	100.0	100.0	100.0
	Repeat/Recur Rate	AMC	Travis AFB	.0	.0	.0	20.0	3.7	7.1	3.5	1.3	.0	1.1	1.3	.0
	WW Log Departure Reliability	AMC	Travis AFB	85.4	91.4	88.3	88.6	92.5	94.3	90.6	91.3	90.8	93.1	90.3	93.4
	HS Log Departure Reliability	AMC	Travis AFB	95.0	100.0	88.9	98.1	95.1	100.0	92.9	93.2	87.7	98.4	97.9	96.4
	Enroute Log Departure Reliability	AMC	Travis AFB	83.6	90.6	88.1	85.7	91.8	92.6	90.1	90.8	91.7	91.5	88.8	92.6
	Delayed Discrepancies - AWM Rate	AMC	Travis AFB	3.5	3.9	4.3	5.2	5.9	5.2	6.9	8.2	7.8	9.1	8.7	7.2
	Delayed Discrepancies - AWP Rate	AMC	Travis AFB	2.5	2.9	2.7	3.1	3.7	5.0	4.9	4.6	3.9	4.1	3.6	3.7
	Delayed Discrepancy Rate	AMC	Travis AFB	6.0	6.7	7.1	8.3	9.7	10.2	11.9	12.9	11.7	13.1	12.4	10.9
	Air Abort Rate	AMC	Travis AFB	.0	.0	.0	.0	.0	.0	.0	.0	.0	.3	.3	.0
	J Divert Rate	AMC	Travis AFB	.8	.0	.4	1.4	.0	.3	1.6	.7	.4	.7	.0	.0
	Dropped Object Rate	AMC	Travis AFB	3.6	.0	.0	.0	11.5	.0	.0	3.4	.0	.0	.0	.0

Figure 11. Global Reach Logistics/A4 Information System/Situational Awareness Report

IV. Results and Analysis

Minitab, version 15, is used for the statistical analysis of the data. In accordance with the guidelines developed by Anderson et al. (2008), regression analysis, forward selection, and best-subsets regression are used to answer the research questions. The data is entered into Minitab to test the various regression models. Table 2 lists the variable abbreviations and their names.

Variable Abbreviation	Variable Name
DR	Departure Reliability
MC	Mission Capable Rate
TNMCM	Total Not Mission Capable Maintenance Rate
TNMCS	Total Not Mission Capable Supply Rate
AvgPoss	Average Number of Aircraft Possessed
AcftAvail	Aircraft Availability
HourlyUse	Hourly Utilization Rate
CANN	Cannibalization Rate
BreakRate	Break Rate
12HrFix	12 Hour Fix Rate
DD	Delayed Discrepancies Rate
Var1	Dummy Variable 1
Var2	Dummy Variable 2

Table 2. Variable abbreviations

Minitab does not allow a categorical factor to be specifically assigned a nominal value. Therefore, variable 1 and 2 are created as indicator variables, also known as dummy variables. Dummy variables are used to represent the different levels of a categorical variable. It is used to model the effect of qualitative independent variables. A dummy variable may take only the value of zero or one. When a qualitative variable has more than two levels, as in this research, care must be taken in both defining and interpreting the dummy variables. If a qualitative variable has *k* levels, *k-1* dummy variables are required, with each dummy variable being coded as 0 or 1 (Anderson, Sweeney, & Williams, 2008).

This research uses regression analysis to help predict DR. With DR as the dependent variable, several independent variables are considered. The individual C-17 bases are also an important factor in predicting the DR. Because each base is a qualitative variable with three levels (Dover, McGuire, Travis), *k-1* or 2 dummy variables are required. Therefore, two new factors are coded into the data set as follows:

Base	Dummy Variable
Dover	0 0
McGuire	1 0
Travis	0 1

Table 3. Dummy variables

Two dummy variables are required because each base is a qualitative variable with three levels, but the assignment of 0-0, 1-0, and 0-1 to indicate Dover, McGuire, and Travis is arbitrary.

Correlation Coefficient Analysis

In multiple regression analysis, a relatively small size of variables can be advantageous in exploring introductory concepts, but it is difficult to illustrate variable selection issues involved in model building (Anderson, Sweeney, & Williams, 2008). This research encompasses 3 bases and considers 12 independent variables over a 12-month period, resulting in 36 data points as shown in Table 4.

DR	MC	TNMCM	TNMCS	AvgPoss	AcftAvail	HourlyUse	CANN	BreakRate	12HrFix	DD	Var1	Var2
0.839	0.915	0.073	0.021	13	0.914	118.3	0.005	0.011	1	0.054	0	0
0.829	0.873	0.118	0.016	12.5	0.841	105.7	0.004	0.025	0.714	0.065	0	0
0.8	0.878	0.117	0.02	12.9	0.873	97.6	0.007	0.007	1	0.082	0	0
0.962	0.856	0.133	0.035	12.4	0.815	125	0.01	0.006	0.5	0.089	0	0
0.907	0.891	0.101	0.015	12.6	0.863	118.2	0	0.017	0.571	0.104	0	0
0.955	0.89	0.093	0.025	11.9	0.818	140	0.002	0.002	1	0.14	0	0
0.857	0.9	0.082	0.023	12.9	0.891	135.5	0.001	0.006	0.5	0.155	0	0
0.959	0.866	0.094	0.07	11.9	0.795	160.8	0.003	0.001	1	0.161	0	0
0.908	0.901	0.082	0.029	12	0.832	152	0	0.003	1	0.177	0	0
0.931	0.892	0.098	0.024	12.3	0.845	141.5	0.003	0.006	0.25	0.176	0	0
0.902	0.927	0.064	0.024	11.9	0.848	118	0.005	0.005	1	0.135	0	0
0.929	0.893	0.094	0.021	11	0.756	106.6	0.004	0.004	1	0.131	0	0
0.839	0.866	0.099	0.051	11.6	0.773	103.1	0.014	0.007	0	0.134	1	0
0.86	0.883	0.095	0.029	10.5	0.712	113.3	0.01	0.016	1	0.128	1	0
0.822	0.882	0.109	0.034	11.6	0.789	107.1	0.003	0.006	0.5	0.158	1	0
0.893	0.873	0.091	0.039	11.5	0.771	131.2	0.011	0.018	0.857	0.167	1	0
0.901	0.894	0.085	0.024	12.8	0.878	111.4	0	0.006	1	0.172	1	0
0.875	0.829	0.148	0.049	13	0.829	104.8	0.009	0.012	0.5	0.172	1	0
0.922	0.875	0.095	0.04	12.7	0.858	110.1	0.018	0.018	0.833	0.188	1	0
0.932	0.9	0.081	0.026	13	0.9	103.7	0.023	0.006	0.5	0.164	1	0
0.918	0.872	0.105	0.03	13	0.872	96.5	0.025	0.009	1	0.155	1	0
0.942	0.847	0.097	0.066	12.9	0.842	101	0.053	0.009	1	0.16	1	0
0.934	0.778	0.19	0.048	12.8	0.769	111.5	0.008	0.032	0.667	0.247	1	0
0.896	0.741	0.221	0.05	11.9	0.678	138	0.02	0.04	0.5	0.354	1	0
0.947	0.865	0.124	0.018	13	0.863	117.5	0	0.013	0.5	0.067	0	1
0.951	0.933	0.067	0.007	12.1	0.868	116.9	0.007	0.015	0.75	0.071	0	1
0.98	0.854	0.112	0.044	12.2	0.801	100	0	0.013	0.333	0.083	0	1
0.917	0.898	0.097	0.029	11	0.76	122.3	0	0.012	1	0.097	0	1
0.973	0.914	0.085	0.027	12	0.846	148.2	0	0.009	1	0.102	0	1
0.921	0.922	0.07	0.012	12	0.848	126.2	0.003	0.003	1	0.119	0	1
0.853	0.894	0.099	0.012	11.2	0.767	120.1	0	0	0	0.129	0	1
0.934	0.89	0.097	0.051	11.6	0.794	122.2	0.008	0.008	1	0.117	0	1
0.873	0.9	0.086	0.033	10.9	0.758	141.9	0.01	0.01	1	0.131	0	1
0.867	0.968	0.029	0.003	11	0.822	146.3	0	0.003	1	0.124	0	1
0.9	0.913	0.075	0.019	11	0.773	128.9	0	0.004	1	0.109	0	1
0.95	0.946	0.053	0.003	11.8	0.856	145.5	0.003	0	0	0.103	0	1

Table 4. DR and 12 independent variables

As a preliminary step, a sample correlation is considered between each pair of variables. Figure 12 is the correlation matrix obtained using Excel.

	DR	MC	TNMCM	TNMCS	AvgPoss	AcftAvail	HourlyUse	CANN	BreakRate	12HrFix	DD
DR	1.000										
MC	-0.038	1.000									
TNMCM	-0.006	-0.958	1.000								
TNMCS	0.176	-0.675	0.499	1.000							
AvgPoss	0.097	-0.288	0.273	0.124	1.000						
AcftAvail	0.061	0.447	-0.433	-0.358	0.727	1.000					
HourlyUse	0.261	0.255	-0.239	-0.093	-0.356	-0.145	1.000				
CANN	0.075	-0.381	0.216	0.516	0.288	0.000	-0.385	1.000			
BreakRate	-0.062	-0.711	0.731	0.268	0.183	-0.336	-0.214	0.229	1.000		
12HrFix	0.045	0.195	-0.236	0.057	-0.115	0.043	0.096	0.075	-0.034	1.000	
DD	0.030	-0.647	0.571	0.474	0.048	-0.417	0.147	0.342	0.455	-0.078	1.000

Figure 12. Correlation coefficients

The correlation coefficient between DR and MC is -0.038, between DR and TNMCM is -0.006 and so on. Looking at the correlation coefficients between the independent variables, the correlation between TNMCM and BreakRate is 0.731; hence if BreakRate were used as an independent variable, TNMCM would not add much more explanatory power to the model. As a rule of thumb, multicollinearity can cause problems if the absolute value of the correlation coefficient exceeds 0.7 for any two of the independent variables (Anderson, Sweeney, & Williams, 2008).

Looking at the correlation coefficients between DR and each of the independent variables can give an indication of which independent variables are, by themselves, good predictors. The single best predictor of DR is HourlyUse, because it has the highest correlation coefficient (.261). For the case of one independent variable, the square of the correlation coefficient is the coefficient of determination (Anderson, Sweeney, & Williams, 2008). Thus, HourlyUse can explain $(.261)^2(100)$, or 6.81%, of the variability in DR.

Estimated Regression with 10-Independent Variables

Although there are potential multicollinearity problems, an estimated regression equation using all independent variables is considered. Results are shown in Figure 13.

```
The regression equation is
DR = - 2.70 + 3.74 MC - 0.05 TNMCM + 0.64 TNMCS + 0.296 AvgPoss - 4.17
AcftAvail
     + 0.00127 HourlyUse + 0.69 CANN - 0.10 BreakRate + 0.0052 12HrFix
     - 0.188 DD


Predictor        Coef   SE Coef      T      P
Constant       -2.704     4.216  -0.64  0.527
MC              3.743     4.632   0.81  0.427
TNMCM          -0.053     1.376  -0.04  0.970
TNMCS           0.640     1.205   0.53  0.600
AvgPoss        0.2960    0.3014   0.98  0.336
AcftAvail      -4.172     4.408  -0.95  0.353
HourlyUse   0.0012689 0.0006362   1.99  0.057
CANN            0.690     1.185   0.58  0.566
BreakRate      -0.099     1.604  -0.06  0.951
12HrFix       0.00519   0.02809   0.18  0.855
DD            -0.1878    0.2366  -0.79  0.435


S = 0.0484094   R-Sq = 20.6%   R-Sq(adj) = 0.0%


Analysis of Variance

Source          DF        SS        MS     F      P
Regression      10  0.015213  0.001521  0.65  0.758
Residual Error  25  0.058587  0.002343
Total           35  0.073800
```

Figure 13. Minitab output for the model involving all independent variables

The 10-variable equation (excluding Var1 and Var2) has an adjusted coefficient of determination of 0.0%. However, the *p*-values for the *t* tests of individual parameters show that only HourlyUse is significant at the $\alpha = .15$ level, given the effect of all the other variables. Investigating the results obtained using just that single variable is shown in Figure 14.

```
The regression equation is
DR = 0.820 + 0.000697 HourlyUse


Predictor        Coef     SE Coef       T      P
Constant      0.82003     0.05439   15.08  0.000
HourlyUse   0.0006968   0.0004421    1.58  0.124


S = 0.0449755   R-Sq = 6.8%   R-Sq(adj) = 4.1%


Analysis of Variance

Source          DF        SS        MS     F      P
Regression       1  0.005025  0.005025  2.48  0.124
Residual Error  34  0.068775  0.002023
Total           35  0.073800
```

Figure 14. Minitab output for the model involving HourlyUse

The estimated regression equation involving only HourlyUse has an adjusted coefficient of determination of 4.1%. It is better than the 10-independent-variable estimated regression, but possibly still not quite as good if determined using other means.

So, how can an estimated regression equation be found that will do the job given the data available? One approach is to compute all possible regressions. That is, develop 10 one-variable estimated regression equations, 45 two-variable estimated regression equations (the number of combinations of 10 variables taken two at a time), and so on. In all, 1,023 different estimated regression equations involving one or more independent variables would have to be fitted to the data.

With Minitab, or any of a number of excellent computer packages available, it is possible to compute all possible regressions. Given a 36 data point set with 12 independent variables, two variable selection procedures, forward selection and best-subsets regression, are used to identify which independent variables provide the best model.

Forward Selection

Figure 15 shows the results obtained by using the Minitab forward procedure for the data using the value of 0.15 for *Alpha to enter*.

```
Forward selection.  Alpha-to-Enter: 0.15


Response is DR on 12 predictors, with N = 36


Step              1        2        3         4
Constant     0.8963   0.8661   0.6688    0.5045

Var2          0.026    0.037    0.047     0.043
T-Value        1.63     2.24     2.68      2.54
P-Value       0.113    0.032    0.012     0.016

TNMCS                   0.90     0.92      0.92
T-Value                 1.84     1.91      2.00
P-Value                0.075    0.065     0.055

AvgPoss                         0.016     0.022
T-Value                          1.49      2.00
P-Value                         0.146     0.054

HourlyUse                               0.00080
T-Value                                    1.83
P-Value                                   0.077

S            0.0449   0.0434   0.0426    0.0411
R-Sq           7.23    15.85    21.32     28.98
R-Sq(adj)      4.51    10.75    13.95     19.82
Mallows Cp     -0.4     -1.4     -1.2      -1.8
```

Figure 15. Minitab forward selection output

In Figure 15, s = √(MSE) has been reduced from .0449 with the best one-variable model (Var2) to .0411 after four steps. The value of R-Sq has been increased from 7.23% to 28.98%, and the recommended estimated regression equation has an R-Sq (adj) value of 19.82%, a considerable increase compared to the 10-independent-variable regression equation using no variable selection procedures.

There are four cases to consider when using the dummy variables Var1 and Var2, assuming that the baseline is Dover AFB.

Scenario	**Result**
1: Neither Var1 or Var2 are significant	All three bases are considered the same
2: Var1 significant and Var2 not significant	McGuire DR significantly different from Dover and Travis
3: Var2 significant and Var1 not significant	Travis DR significantly different from Dover and McGuire

4: Both Var1 and Var2 are significant	Each base is significantly different from the others

Table 5. Potential dummy variable scenarios and results

Based on the data, forward selection chose Var2, but not Var1. That means there is no statistical difference from the baseline, Dover, and McGuire, but there is a difference between Travis and Dover (Capehart, 2010).

Best-Subsets

Figure 16 is the Minitab computer output obtained by using the best-subsets procedure.

Response is DR

Vars	R-Sq	R-Sq(adj)	Mallows Cp	S	MCCM	TNMCM	TNMCS	AvgPoss	AcftAvail	HourlyUse	CANN	BreakRate	12HrFix	DD	Var1	Var2
1	7.2	4.5	-0.4	0.044873												X
1	6.8	4.1	-0.3	0.044976						X						
2	15.9	10.8	-1.4	0.043380			X									X
2	12.3	7.0	-0.2	0.044278				X								X
3	21.3	13.9	-1.2	0.042597			X	X								X
3	21.2	13.8	-1.2	0.042624			X		X							X
4	29.0	19.8	-1.8	0.041117			X	X		X						X
4	26.7	17.2	-1.0	0.041786			X		X	X						X
5	29.9	18.3	-0.2	0.041513			X	X		X	X					X
5	29.3	17.5	0.1	0.041697			X	X		X			X			X
6	30.6	16.2	1.6	0.042023			X	X		X	X				X	X
6	30.3	15.8	1.7	0.042123			X	X		X	X	X				X
7	31.2	14.0	3.4	0.042584	X	X			X	X		X	X			X
7	31.2	14.0	3.4	0.042593	X	X		X		X		X	X			X
8	31.7	11.4	5.3	0.043211		X	X	X	X	X	X				X	X
8	31.6	11.3	5.3	0.043249	X	X	X	X		X	X				X	X
9	32.2	8.7	7.1	0.043884	X	X		X		X	X	X	X		X	X
9	32.1	8.6	7.1	0.043889	X	X			X	X	X	X	X		X	X
10	32.3	5.3	9.0	0.044697		X	X	X	X	X	X	X	X		X	X
10	32.3	5.2	9.0	0.044702	X	X	X	X		X	X	X	X		X	X
11	32.4	1.5	11.0	0.045583		X	X	X	X	X	X	X	X	X	X	X
11	32.4	1.4	11.0	0.045592	X	X	X	X		X	X	X	X	X	X	X
12	32.4	0.0	13.0	0.046559	X	X	X	X	X	X	X	X	X	X	X	X

Figure 16. Minitab best-subsets regression output

The criterion used in determining which estimated regression equations are best for any number of predictors is the value of R-Sq (Anderson, Sweeney, & Williams, 2008). For instance, Var2, with an R-Sq = 7.2%, provides the best estimated regression equation using only one

independent variable; TNMCS and Var2, with an R-Sq = 15.9%, provides the best estimated regression equation using two independent variables. The R-Sq (adj) = 19.8% is largest for the best model with four independent variables: TNMCS, AvgPoss, HourlyUse, and Var2. The second highest R-Sq (adj), 18.2%, contains five independent variables. According to Anderson et al. (2008), "All other things being equal, a simpler model with fewer variables is usually preferred" (p. 723).

Making the Final Choice

The analysis performed on the data is good preparation for choosing a final model, but more analysis should be conducted before making the final choice. As noted before, a careful analysis of the VIF should be done. The following guidelines are used to interpret the VIF:

VIF	**Predictors are…**
1<VIF<2	Not correlated
2<VIF<5	Moderately correlated
VIF>5 to 10	Highly correlated

VIF values greater than 10 may indicate multicollinearity is unduly influencing regression results

Table 6. VIF guidelines

To test the durability of the forward selection process, the VIF of TNMCS, AvgPoss, HourlyUse, and Var2 are examined to prevent using variables that are strongly negatively correlated and have a VIF greater than 5. Figure 17 is the computer output obtained by selecting *variance inflation factors* within Minitab's regression options.

```
The regression equation is
DR = 0.504 + 0.924 TNMCS + 0.0217 AvgPoss + 0.000798 HourlyUse + 0.0433 Var2


Predictor        Coef    SE Coef     T      P    VIF
Constant       0.5045     0.1571  3.21  0.003
TNMCS          0.9244     0.4632  2.00  0.055  1.152
AvgPoss       0.02166    0.01082  2.00  0.054  1.306
HourlyUse   0.0007979  0.0004362  1.83  0.077  1.165
Var2          0.04331    0.01707  2.54  0.016  1.379


S = 0.0411171   R-Sq = 29.0%   R-Sq(adj) = 19.8%
```

Figure 17. VIF output

Since TNMCS, AvgPoss, HourlyUse, and Var2 all exhibit a VIF close to one, the results of the forward selection process can be used to help choose the model.

The best-subsets procedure shows that the best four-variable model contains TNMCS, AvgPoss, HourlyUse, and Var2. This result also happens to be the four-variable model identified with the forward selection procedure. This researcher, in accordance with Maj Shay Capehart (2010), Assistant Professor of Statistics at AFIT, contends that the model appears to be sound. The R-Sq (adj) value is pretty low (19.8%), but one has to realize that there is a lot of noise in this regression, meaning it is very hard to predict a large portion of DR.

V. Conclusions and Recommendations

The results of this research support evidence of a moderately strong relationship between departure reliability and the maintenance metrics: Total Not Mission Capable Supply Rate, Hourly Utilization Rate, and Average Number of Aircraft Possessed. This means that efforts to enhance the focus on these metrics may have effectiveness in a larger effort to improve departure reliability. Consideration of why these three performance measures are statistically relevant along with the significance related to other metrics within the mission generation process must be considered. Additionally, this analysis has value for current guidance as well as potential future research.

Statistical Relevance and Significance

TNMCS is principally driven by spare parts availability. It is based on the number of airframes out for parts. A distinct link exists between TNMCS and CANN rates (AFLMA, 2009). The best situation is for both rates to be as low as possible. Caution should be exhibited not to keep TNMCS low at the expense of increased CANN actions--maintenance should not be driven to make undesirable CANNs just to keep the TNMCS rate low (AFLMA, 2009). According to the AFLMA (2009), questions to be asked when investigating the importance of TNMCS on DR include:

- Why are so many hard-to-get parts being ordered?
- Is the base-stockage level high enough?
- Are old parts being turned in?
- Could the part be fixed on base?
- Even though the current guidance says send it back to depot, can the status quo be challenged?

Operations and maintenance inherently both share responsibility of Hourly Utilization Rate (UTE) because it reflects a combined performance (AFLMA, 2009). If maintenance is not meeting the UTE rate, it means the average number of sorties per aircraft is lower than desired. Scheduling more sorties is not the answer (AFLMA, 2009). According to AFLMA (2009), "The root cause of a low UTE rate may lie in maintenance scheduling practices that result in low aircraft availability, effectiveness of the production effort that repairs and prepares aircraft…or even availability of qualified technicians" (p. 34). It may also mean that other factors, such as weather or climate conditions, have an effect on operations (AFLMA, 2009).

Averaged number of aircraft possessed has a significant corollary to other key maintenance metrics. A low AvgPoss forces a higher real UTE rate on fewer aircraft, possibly compromising two key areas: scheduled maintenance and deferred discrepancies. Higher Recur/Repeat rates may occur. Break rates may also increase and the Fix rate may suffer as well (AFLMA, 2009).

Current Guidance

Per AMCI 10-202V6 (2004), base-level operations commanders are charged with establishing written procedures to review and validate departure reliability information on a monthly basis using the following five-step process:

1.	Detect a change in reliability using the Deviation Accountability Rate formula.
2.	Analyze the data to identify causal factors for the changes.
3.	Document factors impacting reliability and develop a course of action to improve departure reliability.
4.	Implement changes for improving reliability.
5.	Return to step #1 to assess the effectiveness of implemented changes; adjust as necessary, and identify new factors affecting mission reliability.

Table 7. Five-step departure reliability performance process

Additionally, AFI 21-101 AMCSUP1 (2008) directs base-level maintenance commanders to manage the data collection process, review data, and verify analysis for maintenance data collection requirements. Also, commanders are to evaluate and provide trend analysis information.

Both operations and maintenance commanders are instructed with providing data analysis for the processes in which they are responsible; however, explicit guidance detailing how to combine the analysis across the processes is not given. As shown by this paper's research, using regression analysis is a step towards tying maintenance and operations together to give AMC a coherent snapshot of a base's productivity, but also gives base-level commanders a means to improve their mission generation methods.

Future Research

The research completed in this paper does not encompass a wide array of MWSs, bases, or MAJCOMs, but can have significant relevance if used as a springboard for similar situations. The Air Force is consolidating bases, creating flightlines full of different aircraft. For instance, Holloman AFB, NM recently received its first F-22 Raptor fighter aircraft. Now Holloman AFB is home to F-22 Raptors, MQ-1 Predators, and MQ-9 Reapers. Similarly, Hurlburt Field, FL is the host base for several aircraft including C-130s, CV-22s, UH-1s, and U-28s. Holloman AFB is a part of the MAJCOM, ACC and Hurlburt Field is owned by AFSOC. These bases could benefit from a comparable analysis in the same manner this research compiled data found at an AMC MAJCOM base. Although different maintenance metrics may be found to be significant, the same methodology could be applied to increase their homestation departure reliability.

Although the Air Force is creating more ramps with multiple MWSs, "super-bases" such as McChord and Charleston AFB will still continue to exist. The effect of maintenance metrics

on DR at C-17 super-bases compared to single-squadron C-17 bases like McGuire may give HQ AF a quantitative analysis for future basing decisions. For example, a favorable regression analysis at Charleston AFB, shown over an extended period of time, could make a case for moving C-17s from McGuire and Dover to Charleston, consolidating east coast C-17 operations at a one base.

This research paper focuses on homestation DR. Future research of both world-wide and enroute departure reliability can also be analyzed. Introducing these two factors will increase the variability of the model and must be tempered with sound data mining to study the maintenance parameters that directly affect that particular mission generation process. The Logistics Installations and Mission Support-Enterprise View (LIMS-EV) is an application that can be used to provide a single capability to exploit information across all A4 resources to support operational, tactical, and strategic decision making. LIMS-EV supports all types of reporting and analysis requirements using scorecards and dashboards as well as predictive analysis capabilities to all level of users. LIMS-EV will soon bridge the gap between legacy and current data systems to maintain a single enterprise view (Curry, 2008).

Final Thoughts

Continuous improvement between maintenance and operations is not achievable without sound performance measures; however, the data must be analyzed, interpreted, and most importantly, integrated correctly, to make calculated decisions. Pin-pointing which maintenance metrics have the highest relationship to DR will save time, labor, and money within AMC, thus enhancing the overall velocity and precision in AMC's airlift capabilities.

References

AFLMA. (2009). *Maintenance Metrics.* Maxwell AFB: Air Force Logistics Management Agency.

AMC/A3OC, H. (2004). *AMCI 10-202 Vol 6 Mission Reliability Reporting System.* Washington DC: AFDPO.

Anderson, D. R., Sweeney, D. J., & Williams, T. A. (2008). *Statisitcs for Business and Economics.* Mason: South-Western Cengage Learning.

Capehart, S. R. (2010, January 21). Major Vincent M Jacobs GRP. (V. M. Jacobs, Interviewer)

Coyle, J. C., Bardi, E. J., & Novack, R. A. (2006). *Transportation.* Mason: South Western Cenage Learning.

Curry, R. A. (2008, November). *ECSS: The Cornerstone Initiative for eLog21*. Retrieved October 2009, from http://www.ecssmission.com/programinfo/Factsheet/eLog21MM.pdf

Desouza, K. C., & Hensgen, T. (2005). *Managing Information in Complex Organizations: Semiotics and Signals, Complexity and Chaos.* New York: M. E. Sharpe Inc.

HQ AMC/A3OC. (2004). *AMCI 10-202 Vol 6: Mission Reliability Reporting System.* Washington DC: AFDPO.

HQ AMC/A4MMP. (2008). *AMC Supplement to AFI 21-101: Aircraft and Equipment Maintenance Management.* Washington DC: AFDPO.

Johnson, J. P. (2007). *Balanced Scorecard: Aggregating Aircraft Mission Capable Rates.* Dayton: Air Force Institute of Technology.

Jung, C. R. (1991). *Determining Production Capability in Aircraft Maintenance: a Regression Analysis.* Wright Patterson AFB, OH: AFIT.

Kaplan, R. S., & Norton, D. P. (1996). *The Balanced Scorecard: Translating Strategy into Action.* Boston: Harvard Business School Press.

LEAD Technologies, Inc. (2009, Decmeber). Minitab 15. State College, PA, USA.

Oliver, S. A., Johnson, A. W., White, E. D., & Arostegui, M. A. (2001). Forecasting Readiness. *Logistics Challenges*, 3, 31-41.

Pekoz, E. A. (2009). *Manager's Guide to Statistics*. Retrieved Dec 28, 2009, from Probability Bookstore web site: http://smgpublish.bu.edu/pekoz/addin/Excel2007/Stepwise%20Regression.xla

Pendley, S. A. (2008). *C-5 TNMCM Study II.* Maxwell AFB: Air Force Logistics Management Agency.

Simonoff, J. S. (2008). *Statistical Analysis Using Microsoft Excel.* Retrieved December 30, 2009, from NYU Stern Business School: http://pages.stern.nyu.edu/~jsimonof/classes/1305/pdf/excelreg.pdf

REPORT DOCUMENTATION PAGE			*Form Approved* *OMB No. 074-0188*

1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED** *(From – To)*
18-06-2010	Graduate Research Paper	May 2009 – June 2010

TITLE AND SUBTITLE	**5a. CONTRACT NUMBER**
Analysis of C-17 Departure Reliability and Maintenance Metrics	**5b. GRANT NUMBER**
	5c. PROGRAM ELEMENT NUMBER
AUTHOR(S)	**5d. PROJECT NUMBER**
Jacobs, Vincent M., Major, USAF	**5e. TASK NUMBER**
	5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S)	**8. PERFORMING ORGANIZATION REPORT NUMBER**
Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/ENS) 2950 Hobson Street, Building 642 WPAFB OH 45433-7765	AFIT/IMO/ENS/10-07
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) Colonel Steven L. Hopkins Air Mobility Command/TACC/XON 402 Scott Drive Scott AFB, IL 62225	**10. SPONSOR/MONITOR'S ACRONYM(S)** **11. SPONSOR/MONITOR'S REPORT NUMBER(S)**

12. DISTRIBUTION/AVAILABILITY STATEMENT
APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED

13. SUPPLEMENTARY NOTES

14. ABSTRACT
This research analyzes twelve independent maintenance variables and one dependent operations variable for three USAF bases. Minitab, version 15, and Excel are used to analyze twelve months of data, from Dec 08-Nov 09. Forward selection stepwise regression and the best-subsets procedure are used to build predictive models of maintenance metrics' effect on homestation departure reliability of C-17 aircraft at Dover, McGuire, and Travis AFBs. The twelve independent maintenance variables are regressed against one output measure, departure reliability. The regression models and validation results indicate regression models selection of maintenance constraints is consistent between departure reliability and three independent variables: Total Not Mission Capable Supply Rate, Hourly Utilization Rate, and Average Number of Aircraft Possessed. The validity of these findings is limited to the time period covered, but may be generalized across C-17 aircraft at single-squadron C-17 bases within AMC.

15. SUBJECT TERMS
Departure Reliability, Maintenance Metrics, Performance Measures, Regression Analysis, Statistical Analysis, Minitab

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
					Shay R. Capehart, Major, USAF (ENS)
REPORT	**ABSTRACT**	**c. THIS PAGE**			**19b. TELEPHONE NUMBER** *(Include area code)*
U	U	U	UU	52	DSN 785-3636 shay.capehart@afit.edu

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39-18